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Evaluating the Productive Efficiency of Jordanian Public Hospitals

Wasim I. Sultan[1] & José Crispim[1]

[1] University of Minho, School of Economics and Management, Braga. 4710-057, Portugal

Correspondence: Wasim I. Sultan. University of Minho, School of Economics and Management, Braga. 4710-057, Portugal. E-mail: waseem@ppu.edu

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Abstract

Jordan is committed to providing healthcare services for more than a million refugees coming from bordering countries in the last five years and face increasing demand for the services of public hospitals. Their efficiency is a key success factor to manage the unique and complex context effectively. This research investigated the technical and scale efficiency of the Jordanian Public Hospitals. The study applied constant and variable returns to scale input-oriented DEA models to rank hospitals and allocate the factors associated with inefficient operations. The work tested 27 general public hospitals from 2010 to 2014, in total, 135 observations were examined with respect to four input-measures and three output-measures. The output-measures characterize three functional areas; inpatient, outpatient, and ambulance and emergency departments. Further, decomposing the technical efficiency allowed considering for scale effects. Findings revealed that 25 observations out of 135 ones were efficient and constructed the efficient frontier. Eight hospitals in 2014 were on the frontier, but weakly efficient and all suffered slacks. Targets and reference sets were identified to guide improvements. Hospitals were sorted into five performance patterns; promising, declining, stable good, stable poor, and unstable. The number of physicians and outpatient services recorded high slacks. On average, 2013 scored the best performance. Scale analysis shows that a capacity of 160 beds is an optimal production size in Jordan. Inefficient and weakly efficient hospitals can target areas of opportunities for performance improvements. The efficiency of Public hospitals in Jordan was not investigated since 1992. The study was limited to public hospitals from 2010 to 2014.

Keywords: performance, hospitals, DEA, developing countries, Jordan

1. Introduction

The operational environment in Jordan continues to be considerably affected by the security situation in Syria and the influx of the Syrian refugees into the country, as well as by the development in Iraq and Gaza in 2014 (UNHCR, 2016). While the number of inhabitants in Jordan was 9,531,712 in 2015, about 30% of them are not Jordanians, on particular 1,300,000 are Syrians (Statistics/Jordan, 2015). Moreover, due to regional political unsteadiness, there is an unpredictable movement of refugees which places greater demands on the country's infrastructure and health services (Lozi, 2013). According to the United Nations Refugee Agency (UNHCR), Jordan hosted more than a million refugees in 2015. Jordan has granted the Syrian refugees access to services as health and education. The Jordanian Ministry of Health is an operational partner with UNHCR to respond to the refugees' needs (MoH, 2015). Thereby, the Jordanian public hospitals expect more workloads and need to cope with the government commitments toward the refugees; their efficiency becomes a key component of their role.

Data Envelopment Analysis (DEA) methodology, due to its effectiveness, gained acceptance in comparing efficiencies of organizations (Kaitelidou et al., 2016). It is widely used to evaluate hospital performance (Emrouznejad et al. 2008, Xu et al. 2015). This paper measures the technical and scale efficiency of public hospitals in Jordan using DEA. Whilst, advanced methods in operations research had been developed in healthcare applications (Xie & Lawley, 2015), however, DEA is unfamiliar in the literature of the developing countries including Jordan (Shahhoseini, Tofighi, Jaafaripooyan, & Safiaryan, 2011). Most developing countries had based on simple ratio methods (Villalobos-Cid, Chacón, Zitko, & Instroza-Ponta, 2016). Our attempt to fill a gap in the developing countries literature by providing evidence from Jordan. Further, we decompose the factors of inefficiencies and analyze technical and scale efficiencies. We ranked the equally efficient hospitals, then we tested for weak efficiency and identified the benchmark hospitals. The subsection 2.3 introduces the five stages of this work with the aim of reducing inefficiencies.

The Ministry of Health (MoH) in Jordan owns and manages the public hospitals. Their 4693 beds supply 37.8% of the total capacity of hospital beds in Jordan (MoH, 2015). We consider each Jordanian public hospital in every year as a DMU over the period 2010-2014. We analyzed the data of 27 public hospitals; in total, we examined 135 DMUs. We included three functional areas of operations: the inpatient care, the outpatient visits and the emergency and ambulance services. Their scope of operations goes beyond individual patients to influence their families and the whole society (Fitzsimmons & Fitzsimmons, 2006). A better utilization of the hospital resources will enhance the free opportunity to serve additional patients. It is hoped that findings capture the areas that merit more attention for improving performance.

The structure of this paper is as follows: In the following two subsections, we shall review relevant literature applying the DEA methodology and the literature in the developing countries. Thereafter, we shall present the method and case-study description followed by the results. The results and the discussion are combined for each stage of work. Finally, in the conclusion section, we summarize the findings, managerial implications, and the limitations of the study.

1.1 Relevant DEA Literature

The early work of Farrell (1957) brought the development of a powerful methodology to measure relative efficiency of multi-input and multi-output peer production units called DEA by Charnes, Cooper, and Rhodes (Charnes, Cooper, & Rhodes, 1978). Ever since DEA had been widely used to evaluate inefficiencies in many areas. Thousands of research applied DEA to different organizational settings and contexts. Between 2000 and 2014, the DEA research had grown in a fast manner. Four main research fronts in DEA were identified; “two-stage analysis”, “undesirable factors”, “cross-efficiency and ranking”, and “network analysis” (Liu, Lu, & Lu, 2016). This work applies DEA as cross-efficiency and ranking methodology in the context of Jordan.

DEA is a non-parametric approach to estimate the relative efficiency of peer decision-making units DMUs that have multiple inputs and outputs (Cook, Tone, & Zhu, 2014). It is a mathematical linear programming optimization method where inefficient hospitals can benchmark against the best performers. When DEA is applied to hospitals, the hospital under evaluation is considered efficient if and only if it cannot improve some of its inputs or outputs without worsening some of its other inputs or outputs (Cooper, Seiford, & Zhu eds., 2011). Ever since DEA had been widely used to evaluate inefficiencies in many areas, such as but not limited to, the banking industry (Johnes, Izzeldin, & Pappas, 2015), education organizations and institutions (Selim & Bursalıoğlu, 2015), airline companies (Barros & Peypoch, 2009), environmental performance (Zhou, Poh, & Ang, 2016), and hospital operations (Prakash & Annapoorni, 2015). DEA research involved private and public settings (Paradi & Anadol, 2001). Table (1) shows a selected set of DEA-based case studies and the combination of inputs-outputs used to evaluate differences in hospital’s efficiencies.

DEA-based studies provide useful managerial insights on improving performance, and it is an excellent tool to improve service productivity (Sherman & Zhu, 2006). Application to health care and education blossomed in the early days of DEA, however, in hospitals, Sherman (1984) who was the first to use DEA had identified the inefficient hospitals (Liu, Lu, Lu, & Lin, 2013). Review studies of published work on DEA analyzed found that among the most popular application areas are healthcare and education organizations (Emrouznejad et al. 2008, Liu et al. 2013). Hundreds of articles measured the differences in hospital efficiency, most of them applied DEA (Hollingsworth 2008, O’Neill et al. 2008).

Recently, DEA studies tend to analyze the impact of health care intervention programs (Zeng, Shepard, Avila-Figueroa, & Ahn, 2016), technology, settings, and the impact of the crisis on the efficiency of healthcare providers. A study revealed that the adoption of new technology had improved the technical efficiency but did not affect the scale efficiency in the ICUs systems in the Greek public hospitals (Tsekouras, Papathanassopoulos, Kounetas, & Pappous, 2010). Highfill and Ozcan (2016) compared the productivity of hospitals that joined the Medicare’s ACO (Accountable Care Organizations) with non-ACO hospitals in the US. DePuccio & Ozcan (2016) explores efficiency differences between two different settings to deliver medical care; the medical home and nonmedical home hospitals, hospitals in the former model were more efficient. Another study investigated the impact of the crisis on hospital sector and the efficiency of Greek public hospitals applied the DEA to derive hospital efficiency (Kaitelidou et al., 2016). German hospitals were tested for the effect of accreditation on two quality programs, the study found a positive relation between one program of quality standards with efficiency and a negative relation with the other program (Lindlbauer, Schreyögg, & Winter, 2016).

1.2 DEA literature: The Context of the Developing Countries

The lack of data and reporting weaknesses in developing countries had restricted the DEA research (Mogha, Yadav, & Singh, 2016). A study in Iran discussed these barriers of measuring productivity in hospitals and data scarcity when applying DEA and Malmquist index (Nabilou et al., 2016). A cross-national comparison and taxonomy of DEA-based hospital efficiency studies revealed three groups of research based on their country of origin: Europe (25), United States (48), and other countries (6) out of total (79) studies (O'Neill et al., 2008). Very few studies handled the measurement of efficiency in hospitals outside Europe and the US. For exceptional examples are: Canada (Chowdhury, Zelenyuk, Laporte, & Wodchis, 2014), Japan (Kawaguchi, Tone, & Tsutsui, 2014), China (Yang & Zeng 2014, Xu et al. 2015), Turkey (Sahin & Ozcan 2000, Ali 2016), Iran (Hajialiafzali, Moss, & Mahmood, 2007), and the Philippines (Li et al., 2016). Few studies applied DEA in the developing countries. A study was conducted in Pakistan to compare the performance levels between the Islamic and conventional banking systems (Qureshi & Shaikh, 2012). The Malaysian bank industry was investigated by applying DEA to evaluate the efficiency of bank branches (Tahir & Bakar, 2009). Recently, a study applied DEA to evaluate the technical and scale efficiencies of the public sector hospitals in Tunis from 2010 to 2014 (Younsi, 2016). Another study investigated the factors affecting the efficiency of 54 general hospitals in Iran (Kalhor et al., 2016). A study investigated the operations of hospitals in the Sultanate of Oman (Ramanathan, 2005) utilized both DEA and Malmquist Productivity Index (MPI) to rank hospital operations during 1999-2000.

On particular, Jordan case had been studied twice using DEA approach. The first study explored the relation between supply chain practices and technical efficiency of 28 manufacturing firms, the study revealed a strong positive relation (Salhieh, 2011). The second study applied DEA to measure the performance of public hospitals in Jordan (Al-Shammari, 1999). The study analyzed 15 hospitals and used the data of 1991-1993. The author measured the relative efficiency scores, ranked the hospitals and recommended changes required to improve efficiency. Sarkis & Talluri (2002) extended the findings and the methodology and addressed certain issues and utilized an improved method to track the dynamics of performance across the three years. Their method treated each hospital in each year as an observation and then scored all the observations dependently and simultaneously (Boussofiane, Dyson, & Thanassoulis, 1991). They used the model developed by Andersen & Petersen (1993) to rank both efficient and inefficient hospitals across three years.

Table 1. A set of selected DEA studies and their features

Authors and Case Study	Method / Model	Input-measures	Output-measures
(Li et al., 2016) Public Hospitals in the Philippines	DEA-based mathematical model for evaluating performance	- Added exogenous environmental factors	- Included desired and undesired outputs
(Mogha et al., 2016) 36 public sector hospitals of Uttarakhand / India	Input oriented CCR DEA	- Beds. - Doctors. - Paramedical Staff.	- Inpatient days. - Outpatient visits. - Major and minor surgeries.
(Prakash & Annapoorni, 2015) Public hospitals in Tamil Nadu	DEA; variable return to scale, output oriented frontier.	- Beds - Surgeons. - Nurses.	- Outpatient - Total deliveries - Major Surgeries.
(Viola & Benvenuto, 2014) Public Hospitals in South-East Italy	CCR model, input-oriented	- Doctors - Healthcare staff - Non-medical employees. - Number of beds	- The number of adjusted ordinary releases - The number of care days.
(Ozcan, 2008) Non-Federal acute hospitals in Virginia	Quality adjusted DEA. Quality is an additional output measure in the second DEA stage.	- Hospital beds. - Operational expenses. - Total assets. - Total Staff.	- Adjusted Discharges. - Total outpatient visits.
(Kawaguchi et al., 2014) Japanese Municipal Hospitals.	Network DEA, Divisions and all hospital assessments.	- Beds - Doctors. - Nurses. - Administrative.	- Inpatients. - Outpatients. - Emergency.
(Chowdhury et al., 2014) Ontario Hospitals Canada.	Malmquist Productivity Index (MPI), (DEA)	- Staff Hours - Beds Hours - Medical Supply cost - Non-medical supply cost.	- Inpatients. - Outpatients. - Case-mix care days
(Leleu, Moises, & Valdmanis, 2012) ICUs and Hospitals in Florida.	Modified DEA	- Equipment cost. - Staff (FTE). - Nurses (FTE). - Beds. - expenses	- Inpatients days. - Case-mix index
(De Nicola, Gitto, & Mancuso, 2012) Italian Public Hospitals	Bootstrapped DEA.	- The number of physicians. - Nurses. - Beds.	- A number of ordinary discharged patients. - Adjusted case- mix.

2. Methods

2.1 Public Hospitals in Jordan: Settings and Context

The Jordanian healthcare system comprises public, private, charitable and International sectors. The public sector involves (a) Ministry of Health (MoH), (b) Royal Medical Services, (c) Medical services in Public Universities and (d) Health Services in the ministries and government institutions. These service providers operate collaboratively with four council organizational bodies: The Higher Health Council, the Jordanian Medical council, the Jordanian Nursing council and Food and Drug Administration (MoH, 2015).

Out of 12,407 hospital beds distributed in 104 hospitals in Jordan, the MoH owns and operates 31 public hospitals, which supply a capacity of 4693 beds (37.8% of the total capacity), in addition to 1538 different primary healthcare centers. The budget in 2014 accounts for 8% of the Gross Domestic Product (GDP = $36,338 million) as reported by the MoH (2015).We excluded four hospitals from our analysis because they do not conform to common input-output measures. Three of them are Psychiatric hospitals and one is an Obstetrics and Gynecology hospital; they produce different types of services that chart different performance measures.

2.2 Sample and DEA Models

We investigated a sample of 27 hospitals that operate 4226 beds, 90% of the total 4693 public hospital beds. We used the five annual statistical reports published in 2010 to 2014 to get the operational data (MoH, 2015). Table (2) displays some descriptive characteristics of input-output measures of the sample in 2014. The 27 public hospitals are homogenous and share similar production profiles (Villalobos-Cid et al., 2016). They are consistent with the essential assumptions of applying data envelopment analysis (DEA) methodology (Dyson et al., 2001).

The wide dispersion of the input measures motivated us to carry out scale analysis. We followed the approach of Sarkis & Talluri (2002) to include the 135 observations for the years 2010 to 2014. This method meets sufficient discriminatory power of DEA (Cook et al., 2014). The extension method of Boussofiane et al. (1991) allowed us to capture the actual variations of each hospital through simultaneous assessment of all 135 observations. Moreover, the method of Andersen & Petersen (1993) allowed for a global ranking through 1 to 135 including the efficient DMUs.

Traditionally, the input-oriented models are applied to hospital analysis and justified as hospitals serve public healthcare as given and have to manage their resources accordingly (Lindlbauer et al., 2016). It is meaningful to assume that hospital managers have more control over inputs than the outputs (Ozcan, 2008). This work constructs an input-oriented frontier model for attainable performance improvements guided by the space of managers' control (Wang, Wang, Su, & Du, 2015). We applied the input oriented Constant Return to Scale (CRS) model in our measurements (Mogha et al., 2016). Then we apply the Variable Return to Scale (VRS) model to decompose efficiency into the scale and technical efficiencies (Cooper, Seiford, & Tone, 2007).

2.3 Specifications of Input/Output Measures

Dyson et al. (2001) discussed many conditions when using the DEA method and suggested many protocols that deliver robust analysis: (1) State of homogeneity among the DMUs. (2) The number of inputs and outputs when compared to the number of DMUs, (3) The Clear purpose of the DEA exercise, (4) The importance of orientation. A high number of observations serve the sufficient degree of freedom and discriminatory power of DEA. Golany & Roll (1989) suggested a rule of thumb that the number of DMUs is, at least, twice the number of inputs and outputs. Cook et al. (2014) argued that the clear purpose of the DEA exercise helps to define the type of inputs and outputs to be used to fit a clear understanding of the "process" being examined.

The input-output measures characterize three functional areas among the hospitals. We used the following inputs in our analysis: *(I) X1*, the number of beds, *(II) X2*, the number of full-time working physicians, *(III) X3*, the number of healthcare personnel; including pharmacists, nurses, laboratory technicians, radiology technicians and others, *(IV) X4*, the number of administrative employees. The output measures represent the level of public benefits achieved with respect to the three selected functional areas, enlightened by the procedural work of Golany & Roll (1989) and the given literature Table (1). The three main output measures are *(I)* Y1, inpatient days as measured by the total number of annual care days rather than a number of cases to account for case-mix adjustment (Chowdhury et al., 2014). *(II)* Y2, outpatient services as measured by the total number of annual visits, and *(III)* Y3, the ambulance and emergency services as measured by the total annual number of cases served (Kawaguchi et al., 2014). Since the other activities within the hospital (laboratory tests, deliveries, surgical operations, radiology activities…) are highly correlated with the three measure, we did not include them in the set of outputs (Ozcan, 2008). Table (2) displays some descriptive statistics for all measures.

Table 2. Inputs–Outputs: Descriptive statistics of 135 DMU.

Measure (n=27)	Min.	Max.	Mean	Std.
Annual inputs				
Number of beds (X1)	17	1101	150	178
Physicians (X2)	20	642	97	117
Health Cadre (X3)	43	1687	331	282
Administrative Cadre (X4)	13	329	84	59
Annual outputs				
Inpatient days (Y1)	800	268807	35397	47292
Outpatient visits (Y2)	8976	644809	114090	116367
EM and Ambulance (Y3)	0.0	596735	83375	82881

Our approach comprises five stages. *(1)* Assess the existing position of the hospitals (what is the rank of each hospital within a range 1-135?) *(2)* Study efficiency variations over time. *(3)* Directions to improve performance (which hospitals to benchmark?). *(4)* Determine the required reduction and/or increase quantities (what are the target values of inputs and outputs?). *(5)* Analyze the effects of size of operations (what is the scale efficiency of the hospitals?). The following section reports the model, results, and the discussion of each stage. We used Solver algorithm to carry out the linear programming optimization,

3. Results and Discussion

3.1 Stage 1: Efficiency Scores, CRS Model, Input-Oriented Frontier

3.1.1 Results

We analyzed the 135 observations in 135 linear programming optimization iterations, the symbols h_{01} to h_{135} denote DMUs. The number of observations is sufficient to minimize the distortion of the empirical DEA outcomes (O'Neill et al., 2008). We applied the dual CRS model (Charnes et al., 1978), formulation (1.0) shows the applied model.

$$Minimize\ \ \theta_k \tag{1}$$

S.T

$$\sum_{h=01}^{h=135} \lambda_h\ x_{ih}\ \leq\ \theta x_{ik}\ i = 1,2,3,4$$

$$\sum_{h=01}^{h=135} \lambda_h\ y_{rh}\ \geq\ y_{rk}\ r = 1,2,3$$

$$\lambda_h \geq 0\ h = 1,2,..,135$$

Table 3 displays the results. The 25 efficient observations are on the efficient frontier and domain the other inefficient 110 observations.

The radial distance to the constant returns frontier provides a technical efficiency measure for hospitals under assessment. Given the evaluation periods 2010-2014, $h_{k,}$ represents one of the 135 observations, and x_{ik} and y_{rk} are the i^{th} input and r^{th} output of h_k hospital respectively. Running the model will estimate 135 values of relative efficiency scores (θ*). The estimated optimal value of θ is θ* ≤ 1.0 represents efficiency score of the hospital under evaluation. If θ*= *1.0* the hospital is on the frontier and cannot reduce its input proportionally when θ* < *1.0* then the hospital is dominated by the frontier and able to reduce all its inputs proportionally by *(1.0 -* θ*) to become efficient.

Including 135 observations simultaneously to the model allows for addressing the variations of a hospital across two successive years with certainty (Sarkis & Talluri, 2002). Since DEA is a relative measurement method, a change in the efficiency score in the following year of a tested hospital does not necessarily mean a change in its own performance only; changes in the performance of the others may influence the relative position of that hospital. If we carry out an independent analysis for each year, we cannot certainly attribute the changes in the efficiency score of a focal hospital to actual performance change of that hospital.

Table 3. Relative efficiency scores from 2010 to 2014

DMU$_s$	Jordanian Public Hospitals 2014	Beds 2014	2010	2011	2012	2013	2014
			Efficiency Scores from 2010 to 2014				
h_{01}	AL-Basheer	1101	**1.00**	0.91	**1.00**	0.93	0.96
h_{02}	Prince Hamza	433	0.66	0.77	0.83	0.81	0.85
h_{03}	AL-Zarqa	221	**1.00**	0.89	0.97	**1.00**	0.90
h_{04}	Princess Basma	202	**1.00**	0.96	**1.00**	**1.00**	**1.00**
h_{05}	Prince Faisal Bin AL-Hussein	178	**1.00**	0.96	**1.00**	0.98	**1.00**
h_{06}	Jarash	159	0.86	0.84	0.68	0.59	0.76
h_{07}	AL-Hussein / Salt	152	0.82	0.60	0.77	0.65	0.71
h_{08}	Dr. Jameel Al-Totanji	140	0.81	0.87	0.88	0.81	0.90
h_{09}	Ma'an	131	**1.00**	0.95	0.89	0.81	**1.00**
h_{10}	AL-Iman	130	0.91	0.75	0.82	0.69	0.86
h_{11}	AL-Karak	124	0.60	0.62	0.79	0.72	0.58
h_{12}	AL-Nadeem	120	0.73	0.73	**1.00**	0.80	**1.00**
h_{13}	Prince AL-Hussein Bin Abdullah	118	0.12	0.71	0.73	0.61	0.78
h_{14}	Princess Rahma	112	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
h_{15}	AL-Ramtha	110	0.67	0.74	0.90	0.72	**1.00**
h_{16}	Princess Badea'	98	0.93	0.83	0.87	0.93	0.95
h_{17}	Princess Raya	94	0.74	0.83	0.71	0.66	0.81
h_{18}	Ghor AL-Safi	82	0.84	0.85	0.88	0.89	0.93
h_{19}	Mua'th Bin Jabal	75	0.87	0.75	0.85	0.76	0.92
h_{20}	Queen Rania AL-Abdullah	72	0.59	0.60	0.51	0.56	0.48
h_{21}	AL-Mafraq	70	0.84	0.87	0.90	0.95	**1.00**
h_{22}	AL-Yarmouk	67	0.89	0.87	0.93	0.80	**1.00**
h_{23}	AL-Shuneh (South)	60	0.76	0.49	0.54	0.52	0.52
h_{24}	Abu - Obaidah	60	0.96	0.95	**1.00**	0.98	0.83
h_{25}	Princess Eiman\ ma'di	58	0.80	0.80	0.89	0.72	0.87
h_{26}	Princess Salma	38	0.62	0.61	0.63	0.50	0.61
h_{27}	AL-Rueshid	21	**1.00**	0.92	0.80	0.69	0.44

3.1.2 Discussion and Implications

Managers initially need to define their actual position with respect to other performers to improve their processes. Table 3 shows the annual efficiency scores and sheds light on many interesting managerial implications. Efficiency variations categorize the hospitals into five different patterns.

Group 1: promising trend; hospitals *h02, h08, h12, h15, h18, h21* and *h22*. Although the magnitude of improvement was different across the hospitals, *h02* showed a slow rate of improvement but, hospitals *h12* and *h15* changed from 0.73 and 0.67 in 2010 to very efficient (1.0) in 2014. Furthermore, *h21* and *h22* went from 0.84 and 0.89 in 2010 to very efficient in 2014. These hospitals appear frequently in the efficient reference sets as benchmark hospitals Table 5. This group of hospitals shows a good level of efficient management practices and need to keep on their courses. Their policies and decisions demonstrated a right direction of improvements during the last five years.

Group 2: declining trend; hospitals *h07, h23, h24,* and *h27* show a continuous decrease in their scores. Managers may allocate some regular non-value added practices among their hospitals to avoid the propagation of deficiencies. Performance includes a downward trend foreshadowing worse performance and needs corrective actions. Hospital *h27* moves from 1.0 position in 2010 to 0.44 in 2014, it seems that decision makers decided in 2012 to cancel some services (emergency and ambulance services). This decision does not cope with necessary changes associated with the inputs side, a decision made in 2012 needs reconsideration.

Group 3: good and stable performance; hospitals *h01, h03, h04, h05, h09, h14, h16, h19,* and *h25* showed a high level of performance (higher than 0.9) over the five years. Except for *h19* and *h25*, these hospitals are common in their size as large organizations; they operate 41% of the total capacity. Although their inefficiencies score low proportions, though they need more management control actions since these small portions present large absolute deviations in their input and output quantities. Their inefficiency state may be attributed to scale inefficiency and diseconomies of scale. Despite the continuous efficient scores of hospital *h14* operations, it ranks 16, 32, 44, 40 and 57 over the five years respectively. The lagging position of *h14* is attributed to slacks as discussed in the subsection 3.4.

Group 4: poor and stable performance; hospitals *h11, h13, h20* and *h26* show low and stable levels of performance, on average, they score 0.5 and need closer management attention, or reform policies and practices.

Strategic restructuring and process reengineering are suitable methods for this chronic state. Hospital *h13* showed step improvement from 0.12 in 2010 to 0.71 in 2011 then moved consistently; this hospital started working in 2010 which may explain this inconsistent jump in efficiency.

Group 5: Unstable performance; hospitals *h06, h10,* and *h17* show fluctuating behavior. It seems that operations managers do not implement a strategic plan. Regular evaluation reports may help managers to discover the causes behind unstable performance between each two successive years.

3.2 Stage 2: Complete ranking, 135 ranks

3.2.1 Results

To bypass the equal ranking of efficient hospitals by the CRS model in stage (1), we used the holistic ranking model proposed by Andersen & Petersen (1993) that discriminates among the efficient DMUs. This model removes the hospital under evaluation from the constraint set, which allows for efficiency to score greater than (1.0) and provides a principal ranking for both efficient and inefficient hospitals (Sarkis & Talluri, 2002). Formulation (2.0) shows the applied model.

$$Minimize\ \ \theta_k \tag{2}$$

S.T

$$\sum_{h=01}^{h=135} \lambda_h\ x_{ih}\ \leq\ \theta x_{io}\ h \neq k, i = 1,2,3,4$$

$$\sum_{h=01}^{h=135} \lambda_h\ y_{rh}\ \geq\ y_{ro}\ \boldsymbol{h} \neq \boldsymbol{k}, r = 1,2,3$$

$$\lambda_h \geq 0\ h = 1,2,..,135$$

Table (4) shows the ranking position of each hospital across the five years out of 135 scores, henceforth variations in efficiency scores are easy to detect. The sum-ranks and cross-ranks columns summarize an average performance level for each hospital across five years. The means measure the overall annual performance indicator of the public hospitals. Individual managers may benefit from their relative position each year, horizontally in the table. While the Ministry of Health may benefit from the yearly performance of all the group of the public hospitals, vertically in the table.

Hospital *h05* has the best sum of five ranks (72) which reflects the stable good scores of efficiency (1.0, 0.96, 1.0, 0.98, and 1.0) as consistent with high scores in the Table (3). On the other hand, the poor performance of *h26* (0.62, 0.61, 0.63, 0.5, and 0.61) reflects the most lagging position (622) shown in the Table (4). Hospital *h12* shows a promising trend over the five years except for the failure in 2013, its managers can review for changes made in 2013 to avoid future failures.

3.2.2 Discussion and implications

The holistic ranking of 135 observations goes in depth to rank the efficient hospitals which allow for efficient and more objective comparison. Table (4) displays the results. It is evident that the best performer among 135 observations is hospital *h01* in 2012. On average, the hospital operations in 2013 occupy the best performance position as shown by the mean ranks. Managers may review practices and policies in 2013 to develop future plans. The year 2012 scored the lowest mean of efficiency levels which explains.

Table 4. Complete ranking of 135 observations

DMU	2010	2011	2012	2013	2014	SUM	Cross
h01	9	35	**1**	19	17	**81**	**2**
h02	99	59	58	61	48	**325**	**16**
h03	**3**	31	33	**12**	29	**108**	**3**
h04	24	82	39	21	71	**237**	**7**
h05	10	26	8	15	13	**72**	**1**
h06	72	100	90	114	68	**444**	**20**
h07	55	113	94	111	102	**475**	**23**
h08	67	50	54	77	30	**278**	**9**
h09	4	79	56	91	76	**306**	**13**
h10	60	106	51	95	69	**381**	**18**

h11	112	108	118	119	117	**574**	**24**
h12	109	89	28	88	**5**	**319**	**14**
h13	**135**	101	74	115	63	**488**	**22**
h14	16	32	44	40	57	**189**	**4**
h15	107	70	43	93	7	**320**	**15**
h16	18	64	105	49	47	**283**	**11**
h17	86	97	98	104	84	**469**	**21**
h18	103	128	52	73	41	**397**	**19**
h19	34	123	38	66	22	**283**	**10**
h20	122	110	127	120	132	**611**	**26**
h21	80	65	25	96	11	**277**	**8**
h22	36	46	20	83	14	**199**	**6**
h23	78	**133**	126	129	125	**591**	**25**
h24	42	27	2	75	45	**191**	**5**
h25	85	81	62	92	37	**357**	**17**
h26	124	121	**131**	**130**	116	**622**	**27**
h27	6	**23**	53	87	**134**	**303**	**12**
Mean	62.8	77.7	60.4	80.6	58.6		

The best hospitals, when compared to others within the same year, are *h03, h27, h01, h03* and *h12* during 2010 to 2014 respectively, while the worst performers are *h13, h23, h26, h26* and *h27* during 2010 to 2014. Particularly h23 and h26 are in extreme positions, hospital *h26* appears twice as the worst in two successive years. Hospital *h05* shows the best average performance (sum of five ranks 72) over the five years while the best performer *h01* in 2012 shows a sum of 81 over the five years. Again, hospital h12 reveals the best position in 2014 as ranked five. Hospital *h13* in 2010, *h23* in 2011, *h26* in 2012, *h26* in 2013 and *h27* in 2014 are the worst five performers.

3.3 Stage 3: Global benchmarking, Efficient Reference Sets

3.3.1 Results

Each inefficient hospital tracks an Efficient Reference Set (ERS) to catch up the efficient frontier. This set directs the improvement efforts and constructs the composite hospital (virtual) as weighted by the values of their lambdas. The inefficient hospital attempts to become like the composite hospital; that is the convex combination of actual inputs and outputs of reference set hospitals.

Table 5. Efficient reference sets (ERSs) for 19 inefficient hospitals in 2014

	2010	**2011**	**2012**	**2013**	**2014**	∑λ
h01	h_{09} (1.894)		h_{01}(0.5)		h_{12}(2.299)	4.69
h02	h_{03}(0.679) h_{05}(0.261) h_{09}(0.703) h_{14}(0.304)					1.95
h03			h_{04}(0.130)h_{24}(0.197)	h_{03}(0.315) h_{04}(0.222)	h_{12}(0.336)	1.2
h06			h_{12}(0.498)h_{24}(0.204)		h_{12}(0.330)	1.03
h07	h_{04}(0.138)		h_{04}(0.150)		h_{12}(0.35) h_{14}(0.048) h_{21}(0.044)	0.73
h08	h_{05}(0.305)	h_{14}(0.187)			h_{12}(0.492)	0.98
h10			h_{12}(0.66)		h_{15}(0.169)	0.9
h11			h_{04}(0.084)	h_{04}(0.176)	h_{14}(0.139) h_{21}(0.49)	0.45
h13					h_{12}(0.207)h_{15}(0.608)	0.81
h16	h_{09}(0.264)				h_{14}(0.487)	0.75
h17			h_{12}(0.022)h_{24}(0.118)		h_{12}(0.505)	0.64
h18	h_{01}(0.033)	h_{14}(0.052)			h_{12}(0.379)	0.46
h19	h_{03}(0.011) h_{27}(0.411)		h_{12}(0.194) h_{24}(0.422)			1.04
h20					h_{12}(0.255)h_{21}(0.053)	0.31
h23	h_{27}(0.204)		h_{05}(0.0.67) h_{12}(0.043) h_{24}(0.764)		h_{12}(0.037)	0.52
h24	h_{03}(0.051)		h_{24}(0.746)			0.80
h25					h_{12}(0.248)h_{15}(0.169) h_{21}(0.033)	0.45
h26	h_{04}(0.033)h_{27}(0.157)		h_{24}(0.055)		h_{12}(0.049)h_{21}(0.079)	0.37
h27	h_{03}(0.02)		h_{24}(0.072)			0.09

The Global Efficient Reference Sets (ERSs) endeavor to create the benchmark combinations from the best performers within 135 observations. The 19 inefficient hospitals in 2014 attempt to improve their managerial practices according to the related ERSs and lambda values. Table (5) displays the results. As expected, *h12* appears frequently as a reference hospital in 2014 and consistent with evaluations in the Table (3), where *h12* showed a promising trend, and in the Table (4) *h12* ranked as best performer in 2014.

The Lambda (λ_h) is the weight associated with the hospital (h) obtained by the dual linear programming solution shown in equation (1). However, the benchmark is global because the reference set includes managerial behaviors of hospitals within the same year and/or other years.

3.3.2 Discussion and Implications

The measured wastes through five years inspire a wide range of improvement actions to bridge these gaps. It is reasonable to show the ERSs for the inefficient hospitals in 2014 where managerial improvement actions are valid to take place and enhance performance. Table (5) shows a list of efficient reference sets (ERSs); each set provides information about the improvements required by the inefficient hospital to become efficient. For instance, hospital *h16* in 2014 will use a combination of two hospitals *h09* in 2010 and *h14* in 2014 to become efficient. The associated values of lambdas (next to the reference hospital in the Table (5)) *h09* (0.264) and *h14* (0.487) respectively measure the reference hospital's share into the combination. Then, the target inputs and outputs for hospital *h16* are 26.4% of *h09* measures in 2010 plus 48.7% of *h14* measures in 2014. To avoid duplication, we provided these details of *h16* as an example and then we apply an alternative method in section (3.4) to calculate the input-output targets for the hospital.

It is evident that hospital *h12* is the most frequent reference hospital. Hospitals in 2011 and 2013 rarely appear as reference subsets, and only hospital *h14* acts as a reference in 2011. Going back to Table (3) helps us understand these results clearly. Table (3) shows 7.0 efficient hospitals in 2010, only 1.0 efficient hospital *h14* in 2011 (as expected), 6.0 efficient hospitals in 2012, then 3.0 efficient hospitals in 2013 and 8.0 hospitals in 2014; this explains the share of each year to construct the reference sets.

The sum of lambdas in the last column of the Table (5) shows the scale effects of operations of each hospital in 2014. While efficient units exhibit a constant return to scale, the inefficient hospitals exhibit Decreasing Return to Scale (DRS) when $\sum\lambda > 1$ and may benefit from economies of scale. Others, exhibit Increasing Return to Scale (IRS) when $\sum\lambda < 1$ and may suffer diseconomies of scale; a state of weak control. It is evident that all hospitals with 159 beds (*h06*) and more exhibit DRS, and hospitals with less than 152 beds exhibit IRS. It is the optimal productive size of hospital operations. Section 3.5 introduces the scale efficiency analysis.

3.4 Stage 4: Slacks and Target Measures, Ratios of Excess Resources and Deficient Outputs

3.4.1 Results

The input reduction values include both the component of the slacks and the component of proportional reduction by the ratio (1.0 - θ*) from their actual inputs as we are using input oriented frontier. However, the output increment values include only the component of the slacks as augmentation required to the actual outputs. The following formulation (3) linear programming problem calculates the input-output slacks:

$$Maximize \left\{\sum_{i=1}^{i=4} S_i^- + \sum_{r=1}^{3} S_r^+\right\} \quad (3)$$

S.T

$$\sum_{h=01}^{h=135} \lambda_h \; x_{ih} + S_{ih}^- = \theta^* x_{io} \; i = 1,2,3,4$$

$$\sum_{h=01}^{h=135} \lambda_h \; y_{rh} - S_{rh}^+ = y_{ro} \; r = 1,2,3$$

$$\lambda_h \geq 0 \; h = 1,2,\ldots\ldots,135$$

Where "S_i^-" and "S_r^+" denote the slack values associated to the "i^{th}" input and "r^{th}" output of hospital "h" respectively. The negative and positive signs indicate the reductions or increments applied to the actual input-output values. Table (6) shows the results by ratios of the actual measures.

$$X_{io}^{\wedge} = \theta^* \, x_{io} - S_{io}^- \quad (4)$$

$$Y_{io}^{\wedge} = y_{ro} + S_{ro}^+ \quad (5)$$

To consider the weakly efficient hospitals, slack analysis distinguishes between efficient and weakly efficient hospitals (Zhu, 2014). A hospital is efficient if and only if it has θ*=1.0 and all slacks equal to zero. If the efficiency scores θ*=1.0 and, at least, one of the slacks is not zero, the hospital is weakly efficient and can reduce at least one or more of its inputs or increase at least one or more of its outputs to become efficient.

The differences (Δ) between the projected targets and the actual input-output quantities are the possible improvement spaces. The following equations (4 &5) calculate the target values: Table (7) shows the ratios of input targets, input surpluses, output targets and output shortages as a percentage of actual values.

3.4.2 Discussion and implications

Both input and output slacks are factors that contribute to deficiencies, and once determined they will help managers improve their competitive position. It is important for managers to determine the target values, to measure against targets and control their improvement progress. Good operations management allows for decreasing the output shortage levels (the quantities of output slacks) by employing the surplus resources (the quantities of input slacks added to the proportional reduction of inputs). Many hospitals may benefit from this matching policy such as hospitals h02, h18, h19, h20, h21, and h24.

Table 6 and Table 7 show the slacks associated with each input-output measure of each observed hospital in 2014. Although eight hospitals were scored as efficient, it is remarkable that all the efficient hospitals h04, h05, h09, h12, h14, h15, h21and h22 are weakly efficient. Managers of efficient hospitals still have unfinished work to do and reduce their slacks to zero.

Table 6. Input-Output slacks in percentage (2014)

	Actual Inputs				Actual outputs			Input slack %				Output slack %		
	X1	X2	X3	X4	Y1	Y2	Y3	$S1^-$	$S2^-$	$S3^-$	$S4^-$	$S1^+$	$S2^+$	$S3^+$
h01	1101	558	1664	329	268807	564280	596735	5%	3%	-	-	-	21%	-
h02	433	251	648	236	100353	177457	196040	-	-	-	20%	-	81%	-
h03	221	208	644	131	60315	290435	107252	-	34%	5%	-	-	-	-
h04	202	260	632	158	67957	275521	146011	-	33%	-	-	-	19%	80%
h05	178	71	349	73	44469	186665	159193	19%	-	-	-	-	0%	1%
h06	159	65	387	92	26796	123445	127548	12%	-	2%	-	-	0%	-
h07	152	173	429	104	34600	156096	109590	-	36%	-	-	7%	27%	-
h08	140	124	316	83	38842	104871	123104	-	23%	-	-	-	-	21%
h09	131	39	349	50	31693	64711	54960	34%	-	41%	22%	-	-	-
h10	130	54	286	86	21663	98265	129321	4%	-	5%	18%	-	74%	30%
h11	124	140	451	112	24071	103284	41667	-	20%	-	-	-	-	-
h12	120	53	272	46	35748	128240	132000	-	-	-	-	33%	19%	68%
h13	118	60	286	67	19931	52573	126466	-	-	-	-	-	-	-
h14	112	52	294	82	38608	35897	84364	10%	-	1%	-	2%	303%	-
h15	110	55	266	70	21931	86373	163131	-	7%		9%	-	11%	-
h16	98	39	200	69	27838	29599	30862	10%	-	3%	31%	-	-	-
h17	94	38	250	60	19732	81211	75412	-	-	1%	4%	-	-	23%
h18	82	44	209	32	23137	41658	56373	-	16%	10%	-	13%	4%	16%
h19	75	36	155	65	11333	88358	61753	-	-	-	31%	-	24%	-
h20	72	36	181	34	10301	34111	39546	-	4%	2%	-	-	-	-
h21	70	44	320	63	22136	101354	110089	-	17%	30%	-	25%	119%	30%
h22	67	46	226	51	13427	98443	89689	-	14%	-	-	-	-	-
h23	60	34	153	46	7862	48349	33789	-	-	-	-	-	-	-
h24	60	36	171	53	8941	105154	24087	-	-	-	-	47%	46%	71%
h25	58	34	176	29	8090	49736	63927	-	-	16%	-	65%	-	27%
h26	38	32	125	41	6711	37943	28975	-	6%	-	-	-	-	
h27	21	24	46	18	1472	14890	0	-	18%	-	13%	55%	-	*

* Hospital h27 produced zero of the output Y3, the ratio is not applicable; its slack value is 6203 cases.

Hospital *h09* is weakly efficient and suffers relatively high personnel slacks; it warns weak employment policies and may need revision. Hospitals *h12, h18, h21* and *h24* suffer slacks in all of the three outputs and have a chance to improve their efficiency scores by increasing their outputs. Hospital *h15* suffers a large value of 303 % slack in the outpatient services. However, *h14* suffers low levels of slacks of less than 10%.

Decision makers and hospital managers get many beneficial insights from the target and slack results. Although hospital *h01* ranks (1) in 2010, but it ranks (17) in 2014 as explained by deficits in the outpatient services by 21 (about 117,000 visits). The lagging position of *h27* in 2014 reflects high deviations in all the input-output measures; the distribution of loads and resources in *h27* is questionable. Table (7) shows relatively high deviations in the personnel measures (e.g. hospitals h07, h10, h11, and h13). Hospital *h04* has near double the required number of physicians, and hospital *h11* employs additional 87 physicians, 191 health professionals, and 47 administrative employees are beyond its personnel requirements. This state reflects some weaknesses in employment plans, policies or implementation and indicates the need for corrective actions by the ministry officials.

Table 7. Input-Output targets in 2014: differences to targets in percentage

	Estimated Input Targets %				Output Targets%			Input Surpluses %				Output Shortages%		
	$\hat{X}1$	$\hat{X}2$	$\hat{X}3$	$\hat{X}4$	$\hat{Y}1$	$\hat{Y}2$	$\hat{Y}3$	ΔX1	ΔX2	ΔX3	ΔX4	ΔY1	ΔY2	ΔY3
h01	91	93	96	96	100	121	100	-9	-7	-4	-4	-	21	-
h02	85	85	85	66	100	181	100	-15	-15	-15	-34	-	81	-
h03	90	56	85	90	100	100	100	-10	-44	-15	-10	-	-	-
h04	100	67	100	100	100	119	180	-	-33	-	-	-	19	80
h05	81	100	100	100	100	100	101	-19		-	-	-	-	1
h06	64	76	74	76	100	100	100	-36	-24	-26	-24	-	-	-
h07	71	36	71	71	107	127	100	-29	-64	-29	-29	7	27	-
h08	90	67	90	90	100	100	121	-10	-33	-10	-10	-	-	21
h09	66	100	59	78	100	100	100	-34	-	-41	-22	-	-	-
h10	83	86	81	69	100	174	130	-17	-14	-19	-31	-	74	30
h11	58	38	58	58	100	100	100	-42	-62	-42	-42	-	-	-
h12	100	100	100	100	133	119	168	-	-	-	-	33	19	68
h13	78	78	78	78	100	100	100	-22	-22	-22	-22	0	0	-
h14	90	100	99	100	102	403	100	-10	-	-1	-	2	303	-
h15	100	93	100	91	100	111	100	-	-7	-	-9	-	11	-
h16	85	95	92	64	100	100	100	-15	-5	-8	-36	-	0	-
h17	81	81	81	77	100	100	123	-19	-19	-19	-23	-	0	23
h18	93	77	84	93	113	104	116	-7	-23	-16	-7	13	4	16
h19	92	92	92	60	100	124	100	-8	-8	-8	-40	-	24	-
h20	48	43	46	48	100	100	100	-52	-57	-54	-52	-	-	-
h21	100	83	70	100	125	219	130	-	-17	-30	-	25	119	30
h22	100	86	100	100	100	100	100	-	-14	-	-	-	-	-
h23	52	52	52	52	100	100	100	-48	-48	-48	-48	-	-	-
h24	83	83	83	83	147	146	171	-17	-17	-17	-17	47	46	71
h25	87	87	71	87	165	100	127	-13	-13	-29	-13	65	-	27
h26	61	55	61	61	100	100	100	-39	-45	-39	-39	-	-	-
h27	44	26	44	31	155	100	**	-56	-74	-56	-69	55	-	**

** Hospital h27 produced zero of the output Y3 the ratio is not applicable; the ΔY3 is 6203 emergency cases.

3.5 Stage 5: VRS Model, Technical, Pure Technical and Scale Inefficiencies

3.5.1 Results

It is important for the hospital managers to determine their relative efficiency and the factors that contribute to the inefficient behavior in their organizations. In the previous sections, we applied a CRS frontier. We did not consider the scale effects of hospital operations whether they are too small (economies of scale effect) or too large (diseconomies of scale effect). In this section, we apply the VRS frontier developed to satisfy scale effects in the analysis (Banker, Charnes, & Cooper, 1984). The following alternative evaluations of efficiency help managers to capture the components of inefficient operations (Ozcan, 2008).

Since the VRS models always envelop the data more closely than the CRS models (input oriented frontiers), and inefficient DMUs measure the shorter distance to the VRS frontier and scores higher efficiency levels (Dyson et al., 2001). Therefore, the sequential analysis of CRS and VRS models distinguish three types of efficiencies. Table (8) summarizes the calculations and equation (6) shows this decomposition analysis (Cooper et al., 2007):

- Global technical efficiency (TE) as measured by distance to CRS frontiers. It positions the hospital comparative efficiency.

- Pure technical efficiency (PTE) as measured by the distance to VRS frontiers. It demonstrates the cause of inefficient operations.
- Scale efficiency (SE): reflects the portion of inefficiency caused by the given scale of operations.

$$TE = PTE \times SE \tag{6}$$

Table 8. Scale efficiency (SE) scores: 2010-2014

	2010		SE	2011		SE	2012		SE	2013		SE	2014		SE
DMU	θ1*	θ2*	SE	θ1*	θ2*	SE	θ1*	θ2*	SE	θ1*	θ2*	SE	θ1*	θ2*	SE
h01	1.00	1.00	**1.00**	0.91	0.94	**0.97**	1.00	1.00	**1.00**	0.93	**1.00**	**0.93**	0.96	**1.00**	**0.96**
h02	0.66	0.67	**0.97**	0.77	0.81	**0.95**	0.83	0.86	**0.97**	0.81	0.86	**0.94**	0.85	0.89	**0.96**
h03	1.00	1.00	**1.00**	0.89	0.90	**0.98**	0.97	0.97	**1.00**	1.00	1.00	**1.00**	0.90	0.90	**1.00**
h04	1.00	1.00	**1.00**	0.96	0.98	**0.98**	1.0	1.0	**1.00**	1.0	1.0	**1.00**	1.0	1.0	**1.0**
h05	1.0	1.0	**1.00**	0.96	0.97	**0.99**	1.0	1.0	**1.00**	0.98	0.98	**0.99**	1.0	1.0	**1.0**
h06	0.86	0.87	**0.99**	0.84	0.84	**1.00**	0.68	0.68	**1.00**	0.59	0.61	**0.98**	0.76	0.77	**0.99**
h07	0.82	0.83	**0.99**	0.60	0.62	**0.97**	0.77	0.79	**0.98**	0.65	0.67	**0.97**	0.71	0.72	**0.99**
h08	0.81	0.82	**0.99**	0.87	0.87	**1.00**	0.88	0.89	**1.00**	0.81	0.82	**0.98**	0.90	0.90	**1.0**
h09	1.00	1.00	**1.00**	0.95	0.98	**0.97**	0.89	0.91	**0.98**	0.81	0.85	**0.95**	1.0	1.0	**1.0**
h10	0.91	0.93	**0.98**	0.75	0.78	**0.96**	0.82	0.83	**0.98**	0.69	0.73	**0.95**	0.86	0.88	**0.98**
h11	0.60	0.63	**0.95**	0.62	0.65	**0.96**	0.79	0.84	**0.94**	0.72	0.78	**0.93**	0.58	0.61	**0.95**
h12	0.73	0.75	**0.97**	0.73	0.74	**0.99**	1.00	1.00	**1.00**	0.80	0.81	**0.98**	1.0	1.0	**1.00**
h13	0.12	0.46	**0.27**	0.71	0.83	**0.86**	0.73	0.73	**1.00**	0.61	0.63	**0.96**	0.78	0.80	**0.97**
h14	1.00	1.00	**1.00**	1.00	1.00	**1.00**	1.00	1.00	**1.00**	1.00	1.00	**1.00**	1.00	1.00	**1.00**
h15	0.67	0.71	**0.94**	0.74	0.83	**0.88**	0.90	0.91	**1.00**	0.72	0.75	**0.96**	1.00	1.00	**1.00**
h16	0.93	0.98	**0.95**	0.83	0.93	**0.89**	0.87	0.95	**0.92**	0.93	0.96	**0.97**	0.95	**1.0**	**0.95**
h17	0.74	0.83	**0.89**	0.83	0.93	**0.89**	0.71	0.82	**0.86**	0.66	0.78	**0.85**	0.81	0.91	**0.89**
h18	0.84	0.94	**0.90**	0.85	0.97	**0.88**	0.88	**1.0**	**0.88**	0.89	0.96	**0.92**	0.93	**1.0**	**0.93**
h19	0.87	**1.0**	**0.87**	0.75	0.82	**0.91**	0.85	0.86	**0.99**	0.76	0.84	**0.91**	0.92	0.92	**1.00**
h20	0.59	0.80	**0.73**	0.60	0.94	**0.64**	0.51	0.81	**0.63**	0.56	0.84	**0.66**	0.48	0.79	**0.60**
h21	0.84	0.87	**0.96**	0.87	0.92	**0.94**	0.90	0.92	**0.98**	0.95	0.97	**0.98**	1.0	1.0	**1.00**
h22	0.89	0.90	**0.99**	0.87	0.88	**1.00**	0.93	0.93	**0.99**	0.80	0.86	**0.92**	1.0	1.0	**1.00**
h23	0.76	0.96	**0.79**	0.49	0.75	**0.65**	0.54	0.80	**0.68**	0.52	0.73	**0.71**	0.52	0.72	**0.72**
h24	0.96	0.98	**0.98**	0.95	0.96	**0.99**	1.0	1.0	**1.0**	0.98	0.98	**1.00**	0.83	0.84	**0.99**
h25	0.80	0.92	**0.87**	0.80	0.86	**0.93**	0.89	0.89	**0.99**	0.72	0.89	**0.81**	0.87	**1.0**	**0.87**
h26	0.62	0.86	**0.72**	0.61	0.77	**0.79**	0.63	0.79	**0.80**	0.50	0.77	**0.65**	0.61	0.78	**0.79**
h27	1.0	1.0	**1.00**	0.92	**1.0**	**0.92**	0.80	**1.0**	**0.80**	0.69	**1.0**	**0.69**	0.44	**1.0**	**0.44**

Θ1*: The CRS Efficiency Score (Global Technical).

Θ2*: The VRS Efficiency Score (Pure Technical).

SE = Θ1*/ Θ2*: Scale Efficiency Score.

We applied the VRS input-oriented DEA model which requires an additional set of convexity constraint for the linear programming algorithm shown in the formulation (1.0): the sum of lambdas to be one.

$$\sum_{h=1}^{h=135} \lambda_h = 1.0 \tag{7}$$

As expected, the VRS efficiency scores are higher than that of the CRS. The VRS frontier model assigns 36.0 efficient hospitals while the CRS frontier model assigns 25.0 efficient hospitals out of 135 observations. The remaining 110 hospitals' SEs score less than unity, and equal their TE scores. Alternatively, they are efficient in pure technical perspective. These hospitals are: *h01* in 2013 and 2014, *h16* in 2014, *h18* in 2012 and 2014, *h19* in 2010, *h25* in 2014 and h27 in the years 2011, 2012, 2013, and 2014. The CRS inefficiency scores of these hospitals are completely attributed to scale inefficiency as revealed by their shifts to catch the VRS frontier.

3.5.2 Discussion and Implications

Forces of diseconomies of scale affect the operational efficiency of hospital *h01*: *h01* is the largest hospital in the sample; 1101 beds. The manager of hospital *h01* can monitor the outpatient services and review the control procedures to avoid the side effect of their large-size operations. The forces of the economies of scale affect the operational efficiency of the other ten hospitals. On particular, during 2014, hospital managers of *h16, h18, h25* and *h27* may have the chance to restructure their operations and deliver more services.

The SE of all the other hospitals (99 observations) score less than one, and their scale of operation contributes to their TE (CRS-score). Table 8 shows the detailed scores. Attention to manage the slacks will improve SE and the TE will benefit. Hospitals h27 in 2014 shows the worst SE scores. In conformance with our previous discussion; *h27* needs an in-depth revision of their operations.

The SE is the interest of the Ministry of Health to achieve uniform distribution of health resources and workloads. However, the PTE is a hospital's manager interest. Table 8 reveals that the global technical inefficiency, as measured by the CRS model in the first stage of our work, is attributed to scale inefficiency in (11) hospitals. Both the ministry officials and the managers may benefit from this analysis and act for improvements.

4. Conclusion

Among few studies in the developing countries, we applied DEA to evaluate both technical and scale efficiencies of the Jordanian public hospitals. Findings showed that their managers have unfinished work to carry on and may benefit from the results to improve their operations. We followed an analytic methodology of five stages to conceptualize a productivity improvement plan, scoring efficiency, a complete ranking of hospitals, benchmarking sets, deviations from target measures and scale inefficiencies. We got consistent results through the five stages of analysis.

This paper has attempted to gain managerial insights from operational data of 27 public hospitals in Jordan from 2010 to 2014. We analyzed the CRS and VRS frontiers using Data Envelopment Analysis (DEA) methodology. Jordan is a key healthcare provider in the Middle East. The unstable security situation in the bordering countries bears additional amount of work on the Jordanian healthcare system. Efficiency improvement and slack-reduction will help hospitals respond to a possible surge in demand and mitigate the unfavorable effects of work overloads. For example, managing the slacks in outpatient visits of *h01* and *h02* offers additional hundreds of thousands of outpatient visits, and the slacks in emergency services of *h04*, *h12* and *h21* serve additional thousands of trauma cases, such benefits may be passed on to the Syrian Refugees within available capacity.

The year 2013 showed the best annual average performance and shared in three efficient hospitals. However, the year 2014 shared in eight efficient hospitals to construct the efficient frontier. All of eight hospitals are weakly efficient. That is, all the 27 public hospitals have the chance to enhance their efficiency. Their managers may benefit from our results to improve their operations.

This work identifies opportunities for performance improvements, and it is not an improvement end by itself. Public hospitals have the chance to serve additional patients without absorbing more resources in Jordan and can contribute effectively to the national objective of the public health sector. Our results are limited to the public hospitals; further research is required to include the private and the teaching hospitals to generalize findings at the country level.

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